

Eye movement dynamics and cognitive self-organization in typical and atypical development

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Abstract This study analyzed distributions of Euclidean displacements in gaze (i.e. “gaze steps”) to evaluate the degree of componential cognitive constraints on audiovisual speech perception tasks. Children performing these tasks exhibited distributions of gaze steps that were closest to power-law or lognormal distributions, suggesting a multiplicatively interactive, flexible, self-organizing cognitive system rather than a component-dominant stipulated cognitive structure. Younger children and children diagnosed with an autism spectrum disorder (ASD) exhibited distributions that were closer to power-law than lognormal, indicating a reduced degree of self-organized structure. The relative goodness of lognormal fit was also a significant predictor of ASD, suggesting that this type of analysis may point towards a promising diagnostic tool. These results lend further support to an interaction-dominant framework that casts cognitive processing and development in terms of self-organization instead of fixed components and show

that these analytical methods are sensitive to important developmental and neuropsychological differences.

Keywords Interaction-dominance · Self-organization · Development · Autism · Eye movements

Introduction

Researchers in developmental psychology have long recognized the importance of considering development in terms of nested, interactive systems with non-additive, synergistic effects (Bronfenbrenner 1977, 1986; Baltes 1987; Lerner 1991). One particularly striking example is research on gene-environment interaction, which shows that it is insufficient to consider genetics and environment as separate entities with independent effects. In order to provide an adequate account of development, the framework must be based on the interaction between genes and environment (Bronfenbrenner and Ceci 1994; Gottlieb and Lickliter 2007). Nevertheless, traditional cognitive science has sought to understand cognition by breaking it down into separable components such as attention, working memory, and concept knowledge. On this view, cognitive development is conceptualized as the evolution of these discrete components, with individual differences emerging due to differences in one or more of these components. In this report, we motivate and describe an alternative analytical approach that focuses on the dynamics of emergent structure in multiplicative interaction-dominant systems. We then present analyses using this method which show that it is sensitive to important developmental and neuropsychological differences, specifically in the case of autism spectrum disorder (ASD). Finally, we discuss implications

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and future directions for applying such methods to the study of development and individual differences.

Complex-systems approaches to cognitive science: component- and interaction-dominance

The appeal of traditional component-dominant theories has largely to do with methodological expedience: psychologists have powerful scientific methods for evaluating such theories and fewer methods for studying interaction-dominant systems. Of course, the component-dominant approach has been instructive, especially in pointing to the inevitable need for cognitive science to grapple with interaction-driven complexity (Bechtel and Richardson 1993). However, componential explanations have been limited in scope and stand in stark opposition to the growing evidence of multiplicative, interaction-driven phenomena in cognitive science (Ihlen and Vereijken 2010; Stephen and Dixon 2011; Stephen and Mirman 2010; Holden et al. 2009). Interactive systems that span different scales are widely found in many domains of physical science, and the cognitive system is proving to be no exception (Chemero and Silberstein in press). The analytical tools developed in statistical mechanics and computational biology have begun to prove useful for the study of psychological processes (Riley et al. 2011; Dixon et al. 2011). In a similar vein, work in physics and thermodynamics served as key inspiration for the influential parallel distributed processing (PDP) approach to cognition (Rumelhart et al. 1986; Ackley et al. 1985; Hopfield 1982, 1984; Farmer 1990) and concepts from the domain of complex systems have influenced major theories of cognitive development (Elman et al. 1996; Smith 2005; McClelland et al. 2010).

Complex-systems theories of cognition and cognitive development have stimulated the adoption of a new conceptual framework for explaining cognition. Instead of seeking to identify the components of cognition and how these components develop, the focus has moved to the processing dynamics governing cognition and their possible role in the emergence of new self-organized cognitive structures. These self-organizing processes can be framed in terms of stabilization or attractor dynamics (e.g., Spivey 2007): a yet un-organized system is flexible and unstable and able to adopt a variety of possible organizations or structures; once it stabilizes into a particular structure, it becomes more constrained and less flexible. Theoretical frameworks that focus on emergent structure and self-organization have figured prominently in cognitive and developmental science (Elman et al. 1996; Smith 2005; McClelland et al. 2010) and have been applied to a wide variety of phenomena from infant perseverative reaching errors (Thelen et al. 2001) to the emergence of new

problem solving strategies (Stephen and Dixon 2009; Stephen et al. 2009b).

Interaction-dominated, complexity-based cognitive science

More recently, evidence for the distribution of cognition across the brain, body, and context has provided new leverage for a complexity-based approach to cognitive science. Rather than being locked away in the brain, cognition appears to exhibit rampant sensitivity to effects of bodily movement, perceptual exploration, and subtle changes in context (Smith 2005; Chiel and Beer 1997; Turvey and Fitzpatrick 1993; Barsalou 2008; Lipinski et al. 2009). Further, cognition appears to run on a coordination of events at various grain sizes across the body. Cognition has traditionally been understood as unfolding through bodily processes at various scales, whether through quick changes like neural firing, slow changes like cortical maturation, or through the anatomical periphery as in manual coordination (Newell 1990). However, rather than focusing on neural components, attempts to understand development of typical and atypical outcomes alike may need to focus on the high-dimensional connectivities (e.g., Duch and Dubosz 2011). New evidence of multiplicative interactions in cognitive performance suggests that these cognitive processes at different scales of time and space are interdependent (Ihlen and Vereijken 2010). That is, a policy of reducing the cognitive system to distinctly mental or distinctly neural components may be ill-advised. Cognition may depend upon the rich network of multiplicative interactions that leaves all factors interdependent rather than independent. In this view, componential additivity may be the limiting case, and average measures of cognitive performance may be unstable or unreliable (Van Orden et al. 2003).

The complexity-based approach to cognition as fundamentally interaction-dominant depends on closer attention to the distributions of fluctuations throughout the cognitive system, not only in the brain but also throughout the body and the context (Stephen et al. 2009a; Kiefer et al. 2009; Granic and Hollenstein 2003; Granic and Patterson 2006). That is, whereas cognitive science has typically proceeded by comparing mean values on the assumption of additive, white Gaussian fluctuations in cognitive performance, cognitive scientists have become newly concerned with the fact that fluctuations in cognitive performance often depart strongly from additive white Gaussian distributions (Holden et al. 2009; Van Orden et al. 2003; Kello et al. 2008, 2010). Whereas average measures are best for approximating additive (i.e., component dominant) behavior, the distribution at large can often be more informative (e.g., Mayr 1959). Interestingly, changes in the distribution of these fluctuations

appear to predict important differences in cognitive performance (Stephen et al. 2009b, 2010; Stephen and Hajnal 2011). The predictive relationship between fluctuations distributed across the brain-body-context system and cognitive performance suggests that cognition may not depend on irreducible, distinctly mental or neural primitives, but may instead result from non-decomposable interactions across spatial and temporal scales.

Appearance or disappearance of power-law behavior as a signature of structural change

One strategy of the interaction-dominant stream of cognitive research involves testing a continuum of distributions ranging from normal distributions, reflecting pure componential structure, to power-law distributions, reflecting pure interactions and the complete absence of componential structure (Stephen and Mirman 2010; Holden et al. 2009). To understand this continuum, consider random numbers (e.g., a, b, c, \dots), drawn from independent uniform distributions. If very many random numbers are drawn independently and summed together (e.g., $a + b$), then the resulting distribution will be normal. Thus, normal distributions reflect componential structure: they arise from adding the effects of independent variables, a case in which the role of each participating number is always the same. Exponential and gamma distributions reflect slight multiplicative distortion of the additive normal distribution; that is, a system with weakly interacting components¹ (Arellano-Valle et al. 2006;

Kendal 2001). If random numbers are, instead, repeatedly drawn from uniform distributions and multiplied (e.g., $a*b*c*\dots$), then a lognormal distribution will be produced. Lognormal distributions reflect structured interaction-dominant systems because, although the variables are independent, their effects depend on the value of the other variables involved (Holden et al. 2009; Farmer 1990). If the combinatorial process is exponentiation (e.g., a^b), then a power-law distribution will arise. This process also relies on multiplication, but now the elements that are multiplied are not independent: small values are multiplied by small values and large values are multiplied by large values (Montroll and Shlesinger 1982). The interdependence inherent in power law behavior requires that system behavior is interdependent across multiple levels or scales—a system that has no fundamental, characteristic scale² [for a more detailed discussions see Holden et al. (2009); Kello et al. (2010)]. These distributions vary in their tailed behavior, with power laws and lognormal distributions bearing relatively heavy tail, i.e., slow decay of proportions for very large values, with heavier tails for power laws than for lognormal distributions (Speranza and Sollich 2003; Mitzenmacher 2004; Eeckhout 2009; Gong et al. 2005; Krishna et al. 2005).

This spectrum can be construed as reflecting the diminishing plausibility of componential decomposability, ranging from purely additive dynamics to multiplicatively interdependent dynamics. Traditional component-dominant cognitive theories propose essentially constant components (perhaps with some modulation by learning). If cognitive

¹ This weak multiplicative distortion may be expressed in a couple of ways depending on how the distributions are instantiated. Exponential distributions can be generated by the sum of the squares of multiple independent normally distributed variables (i.e., the sum of independent components interacting with themselves, that is, accentuating their own contributions). Gamma distributions are generated by the sum of relatively few exponential distributions; exponential distributions are themselves specific cases of gamma distributions. Gamma distributions may also be generated by dividing the basic exponential distribution function by the gamma function, a continuous generalization of the factorial function (i.e., $x!$), itself a multiplicative transformation. As the number of added exponentials increases towards large limits (i.e., towards the limit of “very many random numbers” as noted in the main text), the gamma distribution converges towards the normal distribution. Alternatively, exponential distributions may be considered as the negative logarithm of uniform distributions in the range (0, 1). In this light, the sum of relatively few exponentials composing the gamma distribution is a logarithm of the product of relatively few uniformly distributed random variables. Because logarithm of repeated multiplication reduces to repeated addition of logarithms, the convergence of gamma distributions to normal distributions holds just the same. Although the values being added affect some aspects of the distribution, in the limit of very large sets of random variables or repeated additions, the distribution will converge to a normal distribution. Thus, in either the gamma or exponential case, no matter how multiplicativity appears in the generation of the distributions, it is quashed by repeated addition of very many random variables (whether those variables are exponential

Footnote 1 continued

or squared normal). That is, skewed distributions following exponential or gamma form will collapse back towards normal distributions and thus reflect much stronger additive than multiplicative relationships among random variables. For this reason, we do not distinguish whether gamma or exponential distributions reflect greater or lesser multiplicativity: gamma distributions may be more multiplicative in general than in the limiting case of the exponential distribution if only because they involve dividing probabilities by values of the gamma function different from 1 (i.e., different from the multiplicative identity), but their convergence to normal distributions suggests that this multiplicativity is ultimately negligible in the largest limits.

² Lack of a characteristic scale refers statistically to the potential divergence of the second moment (i.e., variance). Practically, this point speaks to how confidently we can consider the observed sample to be representative of the yet unmeasured, unobserved behavior. Power-law distributions may not have a finite standard deviation, thus the observed bounds in a particular data set may provide no guarantee that the power-law distributed system will remain within those bounds. The summed behavior of a hierarchy of independent components at different scales may adequately approximate a particular observed power-law-distributed data set, but this system would be committed to the finite bounds of the proposed components. Thus, a multiplicative interdependent system (power-law distribution) and a hierarchy of additive components (multiple additive normal distributions) entail different predictions regarding future observed behavior, both at the lower and upper extremes of the distribution.

organization is less fixed and more softly-assembled, components may form and dissolve and re-assemble into different structures. The degree of organization/re-organization available to the system represents a continuum of componentiality, which is inversely related to multiplicativity and interdependence of the distribution of system behavior. Although both lognormal and power-law distributions are multiplicative, power-law distributions reflect multiplication of interdependent components whereas lognormal distributions reflect multiplication of independent components. Interdependence of components presents a further challenge for empirical decomposability of components (beyond multiplicativity), so power-law distributions are considered as reflecting a system that is less componential (though not more multiplicative) than lognormal distributions. Cognitive structure may be so fluent and regular as to invite the observation of compositionality and componentiality. The key difference between component-dominant and interaction-dominant views is whether this observed componentiality reflects the permanent state of the system (component-dominant) or the emergent result of a subtle confluence of constraints both from the task and from the prior history and development of the cognitive system (Holden et al. 2011; Van Orden et al. 2010).

Cognitive scientists have become interested in what insights the distributions of cognitive performance might provide into the structure of the cognitive system. Because distributions of system behavior may reflect the degree of componential structure, analysis of these distributions provides a measure of system stabilization. That is, because lognormal distributions arise naturally from multiplicative transformations of independent random variables and power law distributions arise from multiplicative transformations of non-independent random variables, lognormal distributions reflect interactivity between processes under more additive constraints than power law distributions. For example, a shift from power-law behavior to lognormal behavior would reflect the emergence of relatively stable, functionally independent components and a shift towards power-law behavior would reflect the breakdown of those components and loosening of functional constraints.

Precisely this type of pattern has been found in velocity profiles (i.e., aggregate distributions of Euclidean displacements) of cell motility. In one example, Takagi et al. (2008) discovered developmental changes in velocity distributions for *Dictyostelium discoideum* (or more familiarly, “slime mold”), which are characterized by generations of “feast and famine” life cycles. During the “feast” phase, *D. discoideum* is unicellular with no differentiable components; during the “famine” phase, *D. discoideum* becomes a multicellular aggregate with distinct anatomical structures dedicated to specific functions (e.g., locomotion or navigation). That is, *D. discoideum* exhibits a transition

to more componential structure once it begins to starve (Chisholm and Firtel 2004). Interestingly, Takagi et al. found that velocity distributions exhibited power-law structure during the unicellular phase of *D. discoideum*, and assumed a more additive distribution, namely the exponential, during the multicellular phase.

Whereas the example of *D. discoideum* suggests a relationship between disappearance of power-law distributions and the emergence of componential structure, a second example dealing with the migration of microglia through hippocampal tissue following spreading depression, a neurological perturbation, suggests a relationship between the appearance of power law distributions and the disorganization of componential structure (Grinberg et al. 2011). Spreading depression manifests as a temporary (i.e., minutes in duration) but abrupt cessation of neural activity in the brain, beginning in one region and propagating outwards in all directions. Sometimes a symptom of head injury, it can contribute to migraines, cerebrovascular disorders, and amnesia (Gorji 2001). Spreading depression can have severe impact on neurological and cognitive components by compromising the structural integrity of the blood–brain barrier (Gursoy-Ozdemir et al. 2004) and the consolidation of memory (Albert 1966; Bures et al. 1974; LaMendola and Bever 1997). One of the effects of spreading depression is to stimulate the migration of microglia in hippocampal tissue, exhibiting velocity distributions with power-law form (Grinberg et al. 2011). Indeed, though microglial migration has been identified as a reparatory response to injury (Lee et al. 2008), microglia can have pathogenic effects on neuronal function (Streit 2000; Carbonell et al. 2005). Grinberg et al. suggested that this power-law distributed microglial migration serves to heighten susceptibility to later spreading depression over a wider range of brain tissue. Thus, power-law distributed migration of microglia may reflect—and possibly later promote—perturbations to componential structure underpinning neurological and cognitive function.

These examples suggest a foundation for interpreting the presence or absence of power-law distributed fluctuations in cognitive performance. Namely, complexity science indicates that the emergence of power-law distributions reflects a “critical” state of loosened constraints in which complex systems are sufficiently disorganized to be poised for a variety of possible new configurations. In this poised state of criticality, dynamics follow similar, generic (i.e., “universal”) laws, regardless of substance (Solé et al. 1999; Stanley et al. 2001; Schertzer and Lovejoy 2004; Papanikolaou et al. 2011). Evidence of power-law fluctuations in cognitive performance has been a crucial motivation for entertaining the possibility that cognition might follow the same generic principles as other physical systems. The current report deals not with cell motility but

with fluctuations in human gaze during visual cognitive tasks, and it presents data suggesting that the departure from pure power-law distribution may indicate the strength of componential constraints on cognitive function.

Fluctuations in gaze exhibit power-law-like distributions

Recent studies of eye movements have found that the distributions of gaze steps recorded during language comprehension and visual cognitive tasks were best fit by power-law-like distributions (e.g., Montroll and Shlesinger 1982), that is, power-law and lognormal distributions (Stephen and Mirman 2010; Stephen et al. 2009c) and that task differences modulated the extent to which the observed distributions were closer to power-law or lognormal distributions (Stephen and Mirman 2010). Stronger task constraints led to stronger evidence of components (shift from power-law to lognormal distributions) and weaker task constraints led to stronger evidence of interdependence of cognitive processes (shift from lognormal to power-law distributions). That is, the extent to which the cognitive system's structure stabilized in response to task (or other) constraints is reflected in the distribution of eye movements.

Differences in gaze fluctuations between typically developing children and children with autism spectrum disorder

Taking a similar approach to studying fluctuations in gaze may be useful in cases of developmental differences in cognitive function, as between typically-developing (TD) children and children with an autism spectrum disorder (ASD). Autism spectrum disorders are neurodevelopmental disorders along a continuum of severity characterized by marked deficits in social and communicative functioning as well as the presence of restricted or repetitive behaviors (American Psychiatric Association 2000). Children with ASD exhibit impairments or abnormalities at all levels of cognitive function: from perception and action to language and communication, to social interaction. In addition to exhibiting this wide range of symptoms, accounts of any one component may be able to account for the full range of symptoms. For example, a low-level perceptual bias in favor of local elements over global shape processing (Behrmann et al. 2006) would predict an impairment of face processing, which could produce an impairment of social interaction and related communication deficits. On the other hand, an impairment of orienting to socially relevant stimuli (Dawson et al. 1998; Johnson et al. 2005; Klin et al. 2002) or simply to eye contact (Pelphrey et al. 2002; Senju and Johnson 2009) would also predict impaired processing of faces.

One hallmark behavior associated with ASD is poorly modulated gaze to the faces of others (Klin et al. 2002; Senju and Johnson 2009). Studies using analyses of overt fixations on pre-defined regions of interest that are assumed to be important for typical processing of faces (e.g., amount of time gazing at the eyes vs. mouth) have found mixed results when comparing TD and ASD individuals, as well as variability in development (Chawarska and Shic 2009; Dawson et al. 2005). On this component-dominant perspective, atypical patterns of face fixation in ASD reflect atypical social functioning and have consequences for language processing and communication but would have no effects on such “low-level” dynamics of eye movements as the distribution of gaze steps. In contrast, the interaction-dominant framework predicts that the cognitive dynamics underlying social and linguistic processing are intrinsically linked with those producing eye movements, so differences in one may be reflected in differences in the other. Because it focuses on system-wide properties, the current approach may be particularly powerful for examining systemic differences, such as would be associated with development in general and in comparisons between typical and atypical development. Recent studies examining basic oculomotor functioning in ASD have found mixed results, with some studies reporting differences between ASD and TD children and others failing to find such differences (Johnson et al. 2005; Brenner et al. 2007; Landry and Bryson 2004). Critically, although these studies did not take complexity-based approaches to studying fluctuations, their motivation closely parallels the motivation for the present study: namely, that oculomotor dynamics may provide a systemic explanatory model of autism.

In this report, we examine the changes in heavy-tailed distributions for gaze steps, and we seek to test whether these changes predict differences in cognitive performance for children with ASD. Specifically, we seek to draw a parallel between, on the one hand, differences in componential stability in the examples of *D. discoideum* and spreading depression discussed above and, on the other hand, the differences in componential stability in cognitive performance. Because gaze-step distributions generally appear to take lognormal and power-law forms, we will take the relative likelihood of lognormal fit over power-law fit as a measure of relative stability of components contributing to cognitive performance.

Neurophysiological evidence of spatial distributions with relatively heavier-tailed behavior in autism

A potentially relevant point of contact between the above cell-motility research into Euclidean displacements discussed above and present concerns may be found in

research on white-matter distributions associated with autism. Autism is associated with an increased volume of white-matter regions in the brain (Herbert et al. 2004). Fahmi et al. (2007) investigated this volume difference in terms of the spatial dispersion of white matter. They used image analysis to calculate Euclidean distance maps expressing the minimal distance of each point in a white-matter region from the region's border. The distributions of distances were strongly tailed for brains belonging to both typical adults and adults with ASD. Fahmi et al. did not report on the relative likelihood of any specific tailed distributions, but they provided evidence of distance maps with significantly heavier tails for brains belonging to adults with ASD. This evidence may be consistent with relatively more power-law (i.e. weaker lognormal) behavior for individuals with ASD and leads us to expect that ASD will be associated with stronger evidence of power-law distribution in gaze steps.

Audiovisual speech perception in children with ASD

A number of studies have shown a reduced role of visible speech information in children and adolescents with ASD (de Gelder et al. 1991; Irwin et al. 2011; Massaro and Bosseler 2003; Mongillo et al. 2008; Williams et al. 2004). Individuals with ASD have been reported to be significantly poorer at speechreading than TD controls (Magnée et al. 2008; Smith and Bennetto 2007). Moreover, children with ASD exhibit reduced visual influence for both mismatched auditory and visual and audiovisual speech in the presence of auditory noise. For audiovisual speech tasks, children with ASD are less influenced by the speaker's face, reporting auditory-only percepts significantly more often than the TD controls (Irwin et al. 2011; Mongillo et al. 2008).

In this report, we describe analyses of distributions of gaze steps that underlie overt fixation behaviors in children with ASD and typically developing (TD) controls recorded while the children observed speaking faces. Eye movements in free viewing are typically considered in terms of fixations and saccades. However, defining when a fixation (or saccade) starts and ends is no trivial matter (Karn 2000; Salvucci and Goldberg 2000), and may specifically be different for typically-developing children compared to children with autism spectrum disorders (Shic et al. 2008). Therefore, since parsing the raw gaze sample data into fixations and saccades may distort the data, and may do so differentially for TD and ASD children, we focus on the underlying raw gaze sample data. Gaze step distribution differences could translate into differences in fixation and saccade properties, but that would be a matter of the fixation or saccade analysis algorithm.

In analyses of distributions of gaze steps, the key variables are (a) what formal distribution provides the best fit to the observed distribution of eye movements, and (b) the

relation between individual differences and the relative goodness of fit of different distributions. An interaction-dominant view of individual differences predicts that individuals whose cognitive systems have self-organized into more stable structures should exhibit distributions that are closer to lognormal and further from power-law and individuals whose cognitive systems that have not stabilized should exhibit distributions that are closer to power-law. We also examine whether eye movement dynamics have any potential as a diagnostic tool for predicting ASD.

Method

Participants

The participants were 43 typically-developing children and 17 children with autism spectrum disorders (ASD) diagnosed prior to the study using DSM-IV criteria by a licensed clinician. Two children (both with ASD) had extremely noisy eye-tracking data (gaze positions appeared to be distributed evenly over the full range of the eye-tracker's recording field with more than 40% of the data points falling outside the screen boundaries), and were excluded from analyses. All participants with ASD met or exceeded cutoff scores for autism spectrum or autism proper on the Autism Diagnostic Observation Schedule-Generic (ADOS-G; Lord et al. 2000). The group of 15 children with ASD was composed of 2 children with Asperger's Syndrome (1 male), 6 children with autism proper (all male), and 7 children with Pervasive Developmental Disorder—Not Otherwise Specified (6 male). All participants completed a language assessment (core language index (CLI) of the Clinical Evaluation of Language Fundamentals (CELF-4), 5–21 years; Semel et al. 2003) and a general cognitive ability assessment (general conceptual ability (GCA) of the Differential Ability Scales School Age Cognitive Battery (DAS); Elliot 1990). Table 1 shows participant details, including sex, age, and assessment performance information.

Procedure

Visual tracking was assessed at 120 Hz sample frequency with an ASL Model 504 pan/tilt remote tracking system with magnetic head tracking. After obtaining parent consent and child assent and completing eye tracker calibration, participants completed a series of audio-visual (AV) speech perception tasks in which they heard a syllable and/or saw a video of a face saying a syllable. The tasks were speechreading (identify syllables spoken in silent videos), speech in noise (identify syllables from noise-added audio paired with video), auditory-visual mismatch (i.e., McGurk and MacDonald 1976), AV synchrony judgments (determine whether

Table 1 Participant information

	Males/ total	Age (years)	CELF: CLI	DAS: GCA	ADOS
TD children					
Mean	30/43	9.63	104.16	105.91	–
SD	–	1.76	10.82	13.98	–
Range	–	7.04–12.54	82–126	73–147	–
ASD children					
Mean	13/15	9.70	83.43	87.87	13.70
SD	–	2.82	21.41	19.88	3.3
Range	–	5.61–15.96	46–114	56–119	10–20

the speaker’s face and voice “talked” at the same time or not), and AV nonspeech discrimination. For a detailed description of the stimuli, tasks, and behavioral results, see Irwin et al. (2011). For the present analyses, the key data were each participant’s distribution of gaze steps during the full experimental session. Data from all tasks were combined because our primary interest was individual differences in AV speech perception without any strong hypotheses about differences between specific tasks. Furthermore, these distributional analyses require large numbers of observations, so combining the data made those analyses more reliable.

Analysis

Gaze step sizes were computed as the Euclidean distance between consecutive gaze position samples recorded by the eye tracker. The frequency distribution of each participant’s gaze step sizes were fit using exponential, gamma, lognormal, and power-law distributions (using the Matlab Statistics toolbox). The ideal distributions mark key points along a continuum as described above. Other points on this continuum could be identified by sums of distributions, but we focus on the parsimonious points defined by standard distributions. In keeping with the view that these distributions reflect a continuum rather than categorically distinct states, the critical measure was goodness of fit for each distribution. Goodness of fit for each distribution was assessed using log-likelihood and relative goodness of fit of two distributions was captured by the difference between log-likelihoods of each fit. Because the difference of logarithms equals the logarithm of a ratio (i.e., $\log(b) - \log(c) = \log(b/c)$), this difference in log-likelihoods is called the log ratio (Singer and Willett 2003).

Results

Gaze-step distributions and individual differences

Of the 58 participants, 51 participants’ gaze step distributions were best fit by the lognormal distribution and 7 (3 TD,

Table 2 Bivariate correlations with lognormality (lognormal/power-law log ratio)

	N	r
Mean gaze step size	58	–0.492***
Individual difference measures		
Age	58	0.319*
CELF:CLI	57	0.312*
DAS:GCA	58	0.405**
ASD (1/0)	58	–0.406**
ADOS	10	–0.457
Behavioral performance measures		
Audio only	53	0.168
McGurk	51	–0.055
Audio in noise	53	0.256
Visual only	53	0.205

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$

4 ASD) were best fit by the power-law distribution. The formal distributions represent points on a continuum and because all of the participants were best fit by either lognormal or power-law distributions (i.e., were between those two points), we used the lognormal/power-law log ratio to measure relative goodness of fit between the two distributions (i.e., their location on the continuum). We will refer to this metric as “relative lognormality” because larger positive numbers indicate a more lognormal (and less power law) distribution and larger negative numbers indicate a more power law (and less lognormal) distribution. To begin exploring relationships between individual differences and eye movement dynamics, we performed simple correlations between relative lognormality and various measures of individual differences (Table 2; A full correlation matrix is provided in the Appendix). Because not all participants were able to complete all tasks, some measures were not available for all 58 participants; the N column in Table 2 lists how many participants completed each task.

None of the behavioral performance measures were statistically reliably correlated with relative lognormality. Since the behavioral tasks were designed to be completed by children with ASD with a range of language and cognitive functioning, they were relatively easy to complete. So this lack of correlation with relative lognormality may, in part, reflect a ceiling effect that compressed the range of behavioral performance. In addition, the relative lognormality measure is meant to capture the degree of stabilization of cognitive structure, but a more stable cognitive structure is not necessarily one that produces better behavioral performance. Just as individuals can exhibit sub-optimal strategies, it is possible that the cognitive system will sometimes self-organize into a stable structure that is sub-optimal for performing a given task. The lack of correlation between relative lognormality and task

performance suggests that the distribution of gaze steps captures cognitive and eye movement dynamics that are a more general property of the individual, not simply a proxy for correct task performance. Further research is necessary in order to understand the relationship between self-organization and task performance on a more trial-by-trial basis (e.g., Stephen and Anastas 2011).

The strongest effect was a negative correlation between mean gaze step size and relative lognormality: participants that tended to make shorter eye movements were better fit by lognormal distributions. This is not surprising, since a key aspect of power law-like distributions is their tail. Furthermore, a greater degree of stabilization of component structure predicts both shorter gaze steps and lognormal (rather than power law) distributions because the development of stable cognitive strategies is associated with a weakening of power-law behavior (e.g., Stephen and Dixon 2009) and participants that have developed stable fixation strategies would make fewer large eye movements, thus producing a shorter overall gaze step size.

Measures of development (age), general cognitive ability (DAS: GCA), and language ability (CELF: CLI) exhibited strong positive correlations with relative lognormality. The presence of an autism spectrum diagnosis was strongly negatively correlated with relative lognormality: compared to typically-developing children, the distributions of eye movements of autistic children were better fit by power law distributions than lognormal distributions. Further, there was a negative correlation between autism symptom severity (ADOS-G score) and relative lognormality, supporting the association between autism and a shift from lognormal to power law distributions (note that the sample size for this analysis was quite small, so this numerically large correlation did not reach statistical significance). Because the typically-developing and ASD groups were not matched in general cognitive and language ability, it was important to examine whether these variables were capturing unique variance in relative lognormality. Hierarchical regression revealed that after mean step size, age, sex, and general cognitive and linguistic ability were included, ASD diagnosis still accounted for significant variance in relative lognormality ($\Delta R^2 = 0.054$, $P < 0.05$). In contrast, after mean step size, age, and ASD diagnosis were included, general cognitive and linguistic ability did not capture additional variance ($\Delta R^2 = 0.028$, $P > 0.25$), nor did sex³ ($\Delta R^2 < 0.001$, $P > 0.9$).

The best model was a three-predictor model (summarized in Table 3), which captured approximately 40% of the variance in relative lognormality (multiple $R^2 = 0.427$, adjusted $R^2 = 0.395$). Each of the three predictors was

Table 3 Results of lognormality regression

	Estimate (SE)	t	Unique variance (%)
Mean Gaze Step Size	-0.0216 (0.005587)	3.9**	15.9
Age	1,183 (430.1)	2.8*	8.0
ASD	-6,489 (2024)	3.2*	10.9

* $P < 0.01$; ** $P < 0.001$

individually removed from the full model in order to evaluate the amount of unique variance captured by that variable. These results indicate that cognitive performance in older children is better able to self-organize into stable context- and task-specific structures, thus exhibiting more evidence of components (distributions that are better fit by the lognormal and less well fit by the power law). In addition, the eye movements of ASD children exhibited less stabilized component structure compared to the TD children.

Can gaze step distributions predict ASD diagnosis?

As a preliminary test of whether eye movement dynamics have any potential to function as a diagnostic tool for predicting individual differences, particularly ASD, we used logistic regression to evaluate whether relative lognormality can predict ASD diagnosis. DAS, CELF, sex, and mean step size were entered into the model. Age was not included because the groups were matched on age. Mean step size did not improve model fit ($\chi^2(1) = 0.525$, $P > 0.4$). Then relative lognormality was added, which improved model fit ($\chi^2(1) = 7.618$, $P < 0.01$). That is, the extent to which a participant's distribution of gaze step sizes was lognormal vs. power-law was a statistically significant predictor of whether that individual was diagnosed with an ASD (beyond what would be predicted by standard measures of language and cognitive ability). In light of the strong correlation between mean step size and relative lognormality, it is noteworthy that, of these two summary measures, only relative lognormality improved model fit in this case as well as the previous case: it was information about tailed behavior rather than information about simple magnitude that predicted differences. Although this was a small and heterogeneous sample of children, this result provides preliminary evidence that suggests eye movements to measure cognitive dynamics may be an effective tool for identifying risk for an autism spectrum disorder.

Discussion

Summary and interpretation of results

Many researchers agree that cognition and cognitive development should be framed in terms of nested, interactive,

³ The null effect of sex may be noteworthy because ASD disproportionately affects boys rather than girls.

self-organizing systems, but there are few analytical tools within psychology for studying these types of systems. Here we have examined the subtle changes in power-law-like distributions to evaluate (a) whether eye movement dynamics in children reflect interaction-dominant processing dynamics and (b) whether this analytical method is sensitive to developmental and neuropsychological differences. We found that the distributions of eye movements of children performing audio-visual speech perception tasks were best fit by lognormal or power-law distributions, which are indicative of interaction-dominant cognitive dynamics in which cognitive structure is self-organized and context-dependent. These results converge with recent studies that examined distributions of eye movements in adults performing a variety of visual cognitive and language tasks (Stephen and Mirman 2010; Stephen et al. 2009c), lending further support to the view of cognition as an interactive, flexible, self-organizing system rather than a component-dominant fixed cognitive structure.

To evaluate the sensitivity of this method to individual differences, the relative goodness of fit of lognormal and power law distributions was examined across individuals. Older children and typically developing children tended to exhibit distributions of eye movements that were closer to the lognormal distribution and further from the power law distribution. Power law distributions are indicative of flexible, scale-invariant systems and lognormal distributions are indicative of interaction-dominant systems with a greater degree of stabilization of structure. As discussed in the introduction, interaction-dominant theories depart from traditional component-dominant theories in that, under an interaction-dominant view, evidence of componential cognitive structure in a particular task context is taken to be evidence of cognitive self-organization and stabilization in response to that context. Following this logic, the present data suggest that development contributes to greater stabilization of cognitive structure in response to task context and that autism spectrum disorders are associated with reduced stabilization in response to task context. This emphasis on the ability of the system to stabilize in response to task context differs strongly from a component-dominant view of cognitive development that would search for maturation of particular components, and from a component-dominant view of neuropsychology that would search for impairment of a particular component. Such system-level accounts may be particularly relevant for system-level individual differences. For example, identifying the “impaired” component in autism has been very difficult because children with autism spectrum disorders exhibit impairments or abnormalities at many levels of cognitive function.

In addition, we found that eye movement distributions that were closer to power law and further from lognormal predicted ASD diagnosis beyond what would be predicted

from standard cognitive and linguistic diagnostic tests and from simple measures of eye movement size. Although this is certainly a very preliminary analysis, this approach has tremendous potential impact. Currently, autism is rarely diagnosed prior to age 3, with the earliest identification at 14 months for about half of children who go on to receive a diagnosis (Landa et al. 2007). In contrast, it is possible to track the eye movements of infants as young as 2 months old (Hunnus and Geuze 2004), with evidence of specific aspects of cognitive and language processing found in 3–8 month olds (Johnson et al. 2003, 2004; McMurray and Aslin 2005). That is, eye tracking is a measure that can be used with very young infants, is sensitive to cognitive and language processes, and reveals dynamics that are related to ASD diagnosis. Studies using traditional analyses of gaze behavior (e.g., proportion of fixations on pre-defined regions of interest on the face) find earliest differences in preschool aged children with ASD (Chawarska and Shic 2009; Dawson et al. 2005). Like other approaches that reveal differences in gaze behavior in infant siblings of children with ASD (Elsabbagh et al. 2009), our approach may provide a convergent method for earlier identification of atypical gaze behaviors associated with this developmental disorder.

Power-law spatial distribution versus power-law distributed temporal correlations

It is important to address a potential point of confusion that these results might raise. Namely, a major theme of interaction-dominant, complexity-based cognitive science has been that the power-law temporal correlations (i.e., $1/f$ noise) is an important signature (or source) of the rich, multi-scale mix of persistence and flexibility characterizing typically-developing cognition (Stephen et al. 2010; Stephen and Hajnal 2011; West and Grigolini 2010; Kloos and Van Orden 2010). That power-law distributions should be associated with the destabilization of complex function might seem discordant with the existing wisdom that power-law temporal correlations are the gold standard for cognitive performance. Indeed, Lai et al. (2010) found that hemodynamic response, which is closely tied to neural activity (Logothetis et al. 2001), showed evidence of significantly weaker $1/f$ noise for adults with ASD when compared with age- and IQ-matched controls. However, it is important to emphasize the difference between the power-law form of an aggregate distribution of fluctuations (e.g., a histogram of Euclidean displacements) and the power-law form of the power spectrum (i.e., $1/f$ noise). The two kinds of power laws reflect different kinds of mathematical views of the data: the former reflects the probability of different sized fluctuations (i.e., a time series' raw values), and the latter reflects the strength of oscillations at different time scales (i.e., a time series' power spectrum).

Not only may estimation be of temporal correlation unstable for power-law-like distributions (Scafetta and Grigolini 2002), as found in gaze steps (Stephen et al. 2009c), but power-law distributions and power-law temporal correlations may actually be mutually exclusive signatures of anomalous diffusive processes (e.g., Upadhyaya et al. 2001). Anomalous diffusion is a driving mechanism underlying chaotic, self-organizing systems in general (Shlesinger et al. 1993). The present results need not be in conflict with previous research (e.g., Lai et al. 2010) but may simply reflect different ways in which chaotic dynamics may manifest in a broad range of cognitive developmental outcomes.

General remarks

The examination of distributions of behavior (specifically, eye movements) can provide insights into cognitive system dynamics that capture individual differences in development and suggest that this analytical method may be useful for early diagnosis of developmental disorders. These results lend further support to an interaction-dominant framework for cognitive performance in which the cognitive system has no fixed components, but rather self-organizes in response to task demands, and demonstrate the utility of this approach for the study of individual differences.

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Appendix

See Table 4.

Table 4 Full correlation matrix

	Lognormality	Step size	Age	CELF	DAS	ASD	ADOS	Audio only	McGurk	Audio in noise	Visual only
Lognormality	–	–0.492***	0.319~	0.312~	0.405*	–0.406*	–0.457	0.168	–0.055	0.256†	0.205
Step Size	0.0001	–	–0.091	–0.402*	–0.343*	0.178	0.074	–0.148	0.105	–0.028	0.044
Age	0.0145	0.4993	–	–0.042	–0.085	0.006	–0.499	0.252	0.099	0.126	0.388*
CELF	0.0180	0.002	0.7590	–	0.560***	–0.543***	–0.070	0.101	0.246†	–0.208	0.102
DAS	0.0016	0.0085	0.5266	0.0001	–	–0.457**	0.467	0.033	–0.009	–0.045	–0.091
ASD	0.0016	0.1819	0.9664	0.0001	0.0003	–	NA	–0.269†	–0.363*	–0.084	–0.236†
ADOS	0.1841	0.8394	0.1424	0.8476	0.1739	NA	–	–0.237	–0.338	0.105	–0.106
Audio only	0.2300	0.2916	0.0684	0.4713	0.8173	0.0510	0.5095	–	0.195	0.537***	0.419*
McGurk	0.7017	0.4618	0.4900	0.0819	0.9496	0.0087	0.3395	0.1712	–	–0.138	0.370*
Audio in noise	0.0645	0.8404	0.3690	0.1348	0.7499	0.5507	0.7878	0.0001	0.3378	–	0.369*
Visual only	0.1414	0.7567	0.0041	0.4689	0.5184	0.0889	0.7861	0.0020	0.0082	0.0066	–

Correlation coefficients are above the diagonal, P values are below the diagonal

† P < 0.1; ~ P < 0.05; * P < 0.01; ** P < 0.001; *** P < 0.0001

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